Digital phenotyping and the development and delivery of health guidelines and behaviour change interventions

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Lovatt and colleagues make the case that drinking guidelines informed by the experiences and behaviours of drinkers are likely to have increased relevance, credibility and efficacy. There is reason to believe that digital technologies such as crowdsourcing, social media, mobile digital devices and biosensing devices measure behaviours such as drinking with a level of detail and on a scale that has not been possible previously. The intensive measurement of behaviours enabled by these approaches, combined with appropriate modelling techniques, can reveal patterns of behaviours that, together with knowledge of the resultant negative or harmful consequences, can inform the development of improved guidelines.

INTRODUCTION

In early 2016 the UK government updated its drinking guidelines for the first time in 20 years [1]. The recommended consumption level was reduced to minimize the risk of diseases such as cancer, and individuals were encouraged to avoid drinking at all on a number of days every week. These new guidelines were developed after a comprehensive review of a wide range of scientific evidence from a number of countries [2]. Recent research by Lovatt and colleagues [3], however, suggests that even health guidelines clearly based on scientific evidence may be perceived as lacking relevance by many adult drinkers. The authors suggest that insights from lay epidemiology, which describe the different approaches individuals actually use to regulate their drinking, should be used in the construction of future guidelines.

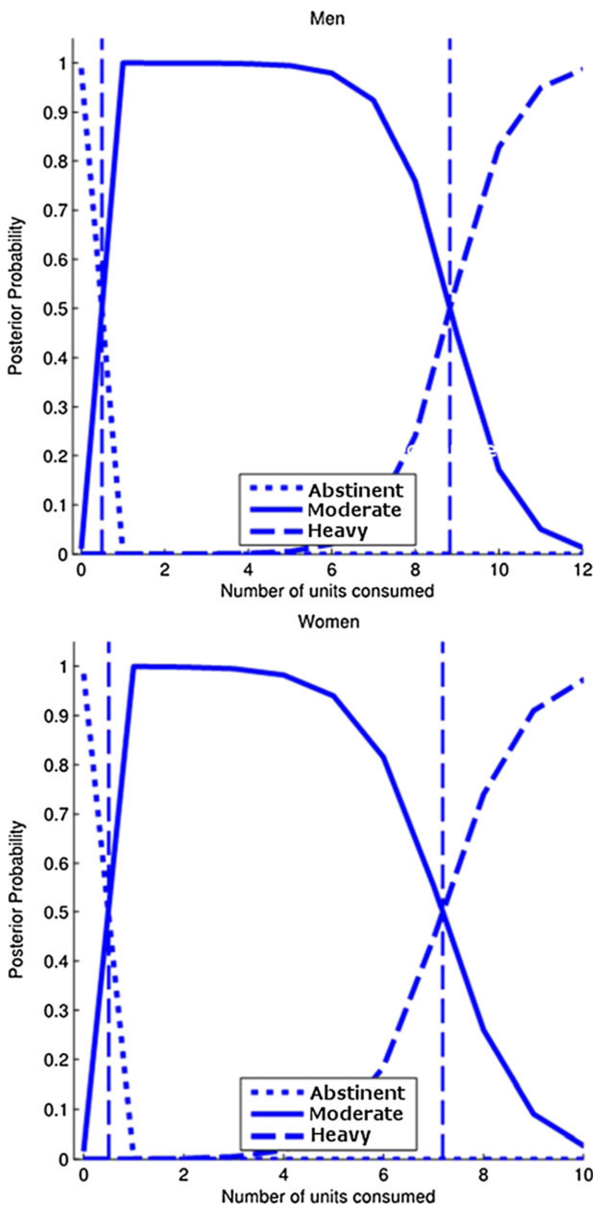
Understanding the true behaviour of individuals is important in the development of effective health guidelines [4]. Knowledge of the negative or harmful consequences of particular patterns of behaviours can inform guidelines, and can potentially enable us to identify subgroups that could be targets for precision prevention. Until recently, measuring life-style health behaviours such as drinking with a sufficient level of detail over long enough periods of time to identify patterns was both time-consuming and expensive. However, recent advances in technology offer the potential to address these challenges. The advent of internet crowdsourcing, ecological momentary assessment applications for smartphones, low-cost on-body sensing technologies and access to social media data all offer new scope for more detailed, larger scale, faster and lower cost measurement. There is a growing recognition, among both researchers [5–7] and funders [8], that new approaches such as these (referred to collectively as digital phenotyping) are set to change the way we measure life-style health behaviours, and deliver interventions targeting these behaviours.

To illustrate how intensive measurement can be used to identify patterns of life-style behaviours, we captured detailed drinking data from a group of undergraduate students (see Box 1). By collecting daily records of drinking behaviour, and applying appropriate modelling techniques (see Supporting information for further details), we identified three distinct drinking modes (abstinent, moderate and heavy), with the heavy drinking mode most probably on Friday and Saturday. These patterns of drinking, combined with knowledge of the negative or harmful consequences they may lead to, could be used to inform drinking guidelines targeting the student population.

With such a modest sample size drawn from an unrepresentative population, these characteristics cannot be applied to the general population. However, extending this type of detailed data capture to a larger and more representative sample could result in drinking guidelines informed by the potential harm arising from real patterns of behaviour in the wider population. Unfortunately, using conventional approaches, this type of study requires considerable time and resources; data collection for the modest study reported here took 5 months to complete, and applying this to a more representative sample would take years rather than months. Digital phenotyping provides a solution. It offers the tools to allow intensively measured behavioural data to be captured on a large scale, faster and at relatively low cost. Examples of some of the digital phenotyping techniques most appropriate to measuring life-style health behaviours are shown described in Box 2.

Passive measurement in particular offers exciting possibilities for measuring life-style health behaviours. The motion sensors found routinely in wrist-worn activity monitors are capable of detecting the signature hand gestures of specific behaviours [17]. Implementing this kind of activity detection on commercially available, low-cost wearable devices (e.g. smartwatches) would enable passive measurement of behaviours such as drinking and smoking on a considerable scale, with little input required from researchers. Using off-the-shelf wearable devices, such as

Box 1 Example of intensive measurement and analysis of behaviour



- Undergraduate drinkers (N = 101) from southwest of England (44 male, mean age 21 years) completed daily diaries recording units of alcohol consumed per day for two weeks.
- Drinking data were analysed using a generative model, with Poisson as underlying distribution.
- Drinking in males and females was best described as three distinct drinking modes (abstinent, moderate and heavy), not as a continuum.
- Boundaries between modes differ for males and females, as shown in the figure, which depicts posterior probabilities of being in each mode.
- Heavy drinking modes were most likely on Fridays and Saturdays for males and females.

smartwatches, also has the benefit of reducing the user burden associated with wearing bespoke sensing hardware. Furthermore, it leverages the manufacturer's significant investment in product design and usability. These are likely to be important factors in ensuring people continue to use any system measuring behaviour.

Passive measurement also holds the potential for capturing behavioural data at a finer level of detail than is achieved typically using conventional diary studies. For smoking, passive measurement could tell us not just the total number of cigarettes smoked in a day, but about the pattern of smoking behaviour over the day. If we take the example of two individuals who smoke the same number of cigarettes a day, they may have very different patterns of smoking. One may smoke heavily in the morning and evening, but not during the working day, while the other may smoke at regular intervals throughout the day. Understanding these differences is important; although the two smoke the same number of cigarettes a day, the differences in the patterns of smoking may mean they respond differently to information in guidelines and behaviour change interventions. Detailed information about individual differences in patterns such as these is therefore likely to be of wide-ranging interest to life-style behaviour research, and will have particular utility in the development of new precision behaviour change interventions.

Box 2 Digital phenotyping techniques for measuring health behaviours

Crowdsourcing

Crowdsourcing is an ideal approach to capturing snapshots of behaviours. Platforms such as Amazon Mechanical Turk (https://www.mturk.com) and Prolific Academic (https://prolific.ac/) enable researchers to recruit large numbers of participants ('crowds') with specific demographic profiles to complete online surveys and experiments. Data from thousands of participants can be gathered within a few days, at a cost of less than a dollar per participant.

Social media

From the digital footprints left by individuals on services such as Twitter and Facebook, researchers can identify temporal and geographic patterns in a wide range of health behaviours, including smoking [9], drinking alcohol [10] and eating [11]. Specific approaches to utilizing social media data vary, from using occurrences of specified keywords (e.g. 'alcohol') to target follow-up telephone interviews [10] to the application of machine-learning techniques to automatically identify words associated with behaviours of interest and, from these, to detect occurrences of individual instances of that behaviour [9].

Mobile digital devices and ecological momentary assessment

To capture detailed patterns of health behaviours within individuals, smartphones are the perfect tool. These devices, optimized for user interaction, are already imbedded in the daily lives of more than 75% of adults in high-income countries such as the United Kingdom [12], with uptake in low- and middle-income countries rising rapidly. Ecological momentary assessment (EMA) techniques [13], which prompt users to respond to simple questions a number of times during the day, are now widely available as apps for smartphones [14]. These EMA approaches, delivered using the increasingly ubiquitous smartphone, are enabling researchers to gather fine-grained information about the life-style behaviours of individuals, in free-living conditions, on a large scale [15].

Passive measurement of behaviours

More recent digital phenotyping developments are opening the door to a new way to capture health behaviour data. Passive measurement refers to automatic approaches to capturing behavioural data, with the individual's consent, but without the need for any active input from the user. Automatically detecting behaviours of interest, often using the sensing capabilities in smartphones or smartwatches, removes the burden of recollecting and inputting information, and offers the potential for high-resolution data, free from the recall errors and reporting biases often associated with life-style health behaviours [16]. Devices equipped with Global Positioning System (GPS) receivers also enable the automatic tagging of the geographical location of behaviours as they occur.

Ambulatory and continuous biosensing

Wearable devices for measuring blood alcohol concentration (BAC) in the wild have been around for some, in the form of ankle bracelets that measure transdermal alcohol concentration (TAC) and relate this to BAC. These are bulky devices, used primarily in law enforcement settings, and are not designed for comfort and ease of use. However, new devices, specifically designed for research in normal free-living conditions are now becoming available. A good example is the Skyn from BACtrack (https://www.bactrack.com), winner of the 2016 NIH Wearable Biosensor Challenge. This is a wrist-worn device the size of an activity monitor, with an easy-to-use application interface, that measures BAC (from TAC) regularly throughout the day and stores data on a smartphone.

Emerging technologies are not only enabling new ways to collect the behavioural data needed to develop more effective health guidelines, but are providing opportunities to deliver this information in increasingly effective ways. This includes, as mentioned, the targeted delivery of specific information addressing individual patterns of behaviour in precision health behaviour change interventions, and also novel approaches to delivering highly relevant guidance in environments in which it is currently not available.

In terms of interventions, smartphones have been used for some time to deliver a range of behaviour change interventions [18]. Recently, researchers have been using the increasing sensing and networking capabilities of smartphones to develop interventions that target delivery of messages and information to individuals at precisely the moments they are most effective. An example of these just-in-time interventions is the Q Sense context-sensitive smoking intervention application (app) [19], which uses geofencing techniques to target messages to individuals attempting to quit when they are in proximity to locations at which they have smoked previously. The GPS sensor in the smartphone allows the individual to tag locations at which they have smoked previously. The system then detects automatically when the person is within a certain distance of that location, and this triggers delivery of a message supporting their quit attempt.

This same approach could be used for any life-style behaviour, including drinking alcohol: locations at which the individual has drank previously and may be tempted to drink again could be tagged, so that delivery of targeted behaviour change interventions could be triggered automatically when the individual is close to these places. The content of those interventions could be informed by drinking data from digital phenotyping, perhaps focusing on preventing one mode of drinking behaviour progressing to another mode with higher consumption.

A development of this approach would be to combine geofencing with passive measurement. Passive measurement, using a smartwatch-based system paired with the smartphone, could automatically detect the behaviour of interest (e.g. smoking or drinking) so that the geographical location of the behaviour could be tagged without any manual input from the individual. This would mean that both key aspects of the system were automated—the generation of the list of high-risk locations and the subsequent detection of proximity to these locations that triggers an intervention.

New technology may also enable delivery of health guidelines and information in places where it is currently absent. Taking alcohol as an example, in many countries bottles and other containers of alcoholic drinks are already labelled with basic information about alcohol content, and the European Union Alcohol Strategy for 2016–22 is likely to increase the information and guidance labelling required. However, there are many situations in which individuals consuming alcohol do not come into contact with these labels, perhaps most notably in bars and public houses, where drinks are served in glasses. A recent study suggests that for health warnings on glasses to be effective in achieving behaviour change, the information displayed will need to be highly relevant to the individual, and not simply generic [20]. One approach that could increase the relevance is for information and messages to be tailored dynamically to the environment and the individual. New thin film, low–power display technologies (such as that being developed by Folium Optics, http://www.foliumoptics.com/) offer the potential for low cost, flexible screens that could be attached to glasses to display dynamic text and graphical information. These could be powered using very small- form power cells, inductive charging or even kinetic energy recovered from glass movement. Near-field communication, a short-range wireless technology found routinely in smartphones, could enable a 'smart' glass to connect to the smartphone of an individual to access basic profile information that could be used to tailor messages on the basis of, for instance, the person's sex or age (i.e. certain demographics may be more responsive to information about increased calorie intake than to potential health implications). Sensors within drinking glasses that monitor liquid levels (e.g. those found in devices such as the Vessyl, www.vessyl.com) could also track the rate of drinking and total volume of drink consumed. The messages displayed could be updated on the basis of this real-time 'within drinking session' data, perhaps targeting specific information to those drinking heavily.

Clearly, with these more personalized approaches to capturing behavioural data and delivering information and interventions there will be issues concerning security and privacy of data and a range of other ethical considerations. In addition, it may be optimistic to assume that individuals engaging in risky behaviours will be willing to provide unlimited access to information about their location and activities. However, recent research indicates people are increasingly willing to share data about themselves in exchange for a range of different types of benefits [21]. The challenge will be to identify benefits that are attractive enough, without having any detrimental health effects. In terms of behaviour change interventions, it is also worth noting that there will be many ways for individuals to avoid or block unwanted intervention messages. In particular, individuals using interventions that require them to wear sensors or other devices will need to be willing to engage with the interventions and their various mechanisms.

In summary, digital technologies are providing new tools for measuring life-style health behaviours. Behaviours such as drinking can now be measured with greater resolution and accuracy, in larger groups, at lower cost than ever before. Data captured using these digital phenotyping techniques, when analysed with appropriate modelling techniques, can reveal patterns of behaviours, and potentially identify subgroups within a population with specific patterns of behaviours. These patterns of activity, when combined with information about the resultant negative or harmful health consequences, can inform the construction of health guidelines based on real behaviour. Emerging technologies are also enabling new approaches to delivering this information in precise ways to maximize its effectiveness, and to help change behaviours.

Declaration of interests

None.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web-site:

Figure S1 BIC Values for Models with Different Numbers of Modes.
Table S1 Modes of Drinking Behaviour.

